Learned Inattention and its Impact on Categorization in Children and Adults

Research Thesis

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Abstract

Category learning is vitally important to human cognition because it enables people to apply learned information to new situations. Category learning greatly benefits from the ability to focus on what is relevant to category discrimination and ignore what is irrelevant, or *selective attention*. However, a consequence of this ability is *learned inattention*; this is a tendency to continue ignoring information that was previously learned to be unimportant, even after it becomes relevant. This pattern of attention is in contrast to distributed attention, demonstrated in infants and young children, where everything is observed with equal importance. An important question remains: when in development does category learning shift from being sub-served by distributed attention to being sub-served by selective attention. We investigated these phenomena through two experiments: first, we used behavioral testing with 5-year-old children and undergraduates; and second, we used eye-tracking technology with a separate sample of undergraduates. All participants were tasked to learn two artificial categories which had two features that were relevant to category discrimination and two features that were irrelevant. Participants were advised to focus on the features of the stimuli but they were not told which features were relevant or irrelevant. They were also given feedback on their accuracy during learning trials. In a second phase, participants had to learn two new categories where the former irrelevant and relevant features were switched. Participants were alerted that a change had occurred, but they were not told that the features changed in relevancy. The experiment was designed to run on both adults and children, framed as a computer game. Data from Experiment 1 indicated that both adults *and five year old children* were able to use selective attention to learn these categories. Eye tracking data from Experiment 2 supported these results by indicating that adults were in fact selectively attending to relevant features in order to discriminate categories.

Introduction

One of the major cognitive tools that people use in order to make sense of the world is the process of sorting information into categories. This enables people to apply learned information to new situations. There are numerous reasons that this skill is important to human cognition; for example, if someone knows that they are allergic to clams, they would likely not try the new mussel dish at their favorite restaurant. Based on previous negative experiences with clams, they would likely assume that this new situation would be similar to what they already suffered. The ability for humans to interpret unfamiliar information by relating it back to previously formed categories gives us a mental shortcut that allows us to make faster judgments.

In any type of categorization, there are qualities of a category that are important to distinguishing it from other categories (category discrimination), and there are others aspects that are not important. Relating back to the previous example, if that individual saw a seafood that they have never seen before and they were trying to determine if it was shellfish, it would be important to pay attention to certain qualities, such as if it has a shell, over other qualities, such as the size, color, or shape of the object. In order to efficiently learn categories, it may be necessary that people be able to pay attention specifically to the properties that are relevant for category discrimination over properties that are unimportant. Most category learning theories argue that category learning benefits greatly from the ability to focus on what is relevant to category discrimination and ignore what is irrelevant, or *selective attention* (e.g. Hoffman & Rehder, 2010; Kruschke, 1996; Sloutsky, 2010).

The ability to attend selectively offers a benefit to quick category acquisition; it allows individuals to focus on information that is category-relevant and, additionally, ignore information that is category-irrelevant. For example, if a task involved objects that must be sorted into circles and squares, it would be advantageous to pay attention to the shape of the figure over the size, orientation, or other irrelevant dimensions. Though selective attention would seem to have many benefits to learning, it also results in measurable costs. One of these consequences is the occurrence of *learned inattention* (Kruschke, 1992). This is a tendency to continue ignoring information that was previously learned to be unimportant. Due to this tendency, if it were required that an individual shift their attention back to features that were formerly irrelevant, a detrimental effect of selective attention may be incurred. If participants spent some time sorting figures by shape and were then asked to sort them by color, they would be able to make this change but there may be a cost – a dip in accuracy or they may slow down in their decision making – as they must learn to shift their attention back to something that they were previously ignoring.

Evidence suggests that adults show a cost of learned inattention to a feature that was switched from being irrelevant to relevant in a novel category (Hoffman & Rehder, 2010). When adults attend selectively during learning in one category discrimination task, they will encounter a cost of this behavior when learning a second, competing category discrimination.

While it has been demonstrated that selective attention is significant to category learning in adults, it is less clear what effect selective attention may have on the category learning processes earlier in development. In one study, (Best, Yim, & Sloutsky, 2013) infants and adults were both presented with similar experiments examining the cost of selective attention. In these experiments, the participants were presented with related categories, and between phases of category learning the relevant and irrelevant information was switched unannounced. The results suggested that adults demonstrate a cost of selective attention right after the switch occurs, as demonstrated by slower learning after the switch. No such costs were observed in infants. Additionally, the eye tracking data showed that learning in adults was accompanied by shifted attention to relevant features, whereas learning in infants was accompanied by attention distributed between relevant and irrelevant features. This tendency in infants was not a product of randomly looking around the screen, but, rather, the data suggested that the more distributed attention used by infants actually made the categorical switch easier for them. Preliminary data (Best, Robinson, & Sloutsky, 2012) also suggested that four-year olds demonstrate the same distributed attention of infants.

The question remains of at which point in development category learning strategies shift from being sub-served by distributed attention to being sub-served by selective attention. In this study, we aimed to investigate the magnitude of the effect of learned inattention on category learning across development. We designed two experiments to look at this question. The first experiment consisted of conducting a similar study with five-year olds and undergraduates. This study contained two relevant phases. In the first phase, the participants were asked to learn two artificial categories, with only feedback and repetition to guide their learning, and then, in a second phase, the previously irrelevant information became category relevant. The second experiment consisted of running the same study design on a new population of adults while also using eye-tracking technology. In the first experiment, we looked for the use of selective attention by inferring what participants were focusing on from accuracy data. In the second experiment, we wanted to confirm that accuracy data was accurately reflecting the use of selective attention. We aimed to do this by examining what features of the categories participants were looking at as they learned. Eye-tracking technology was used to measure exactly where participants were looking on the screen to determine what they were paying attention to.

At the start of this project, we had several working hypotheses. For Experiment 1, we hypothesized that adults would selectively attend to relevant information to learn categories. Building on this, we further hypothesized that adults would should a cost of learned inattention immediately after the categorical learning switch. This, we expected, would result in a drop in accuracy at the start of Phase 2 (when the participants would be learning the switched categories). For child participants, we predicted a different pattern of results. Our hypotheses were that five year old children would distribute their attention while learning categories (much like infants and four year olds) and that they would therefore not demonstrate a cost of learned inattention. We thought that children might have less difficulty with the category switch and that their accuracy would not suffer as much as adults. Finally, in Experiment 2, we wanted to add weight to our previous hypotheses. We expected that adults would still be selectively attending to relevant information to learn categories; accordingly, we hypothesized that the eye tracking data would show increased relative looking time to relevant features as learning proceeded. After the category switch, we hypothesized that the cost of learned inattention would again be demonstrated by lower accuracy data. Additionally, we predicted that there would be maintained relative looking time to the previously relevant features after they became irrelevant.

Experiment 1

Method

Participants

For this study, we recruited 21 adult participants who were undergraduate students at The Ohio State University. They were all enrolled in an introductory psychology course, and they received course credit for participation. In addition, we ran 27 children from elementary schools and preschools in and around Columbus, OH. All of the children were five years old at the time of testing. I did not put strict month requirements on subject eligibility; any child that was five years old on the day of testing was considered eligible. The group of child participants consequently ranged from children who had recently turned five through children who were almost six. 14 children were elementary school students at time of testing, and the remaining 13 children were in preschool at time of testing. Consent was obtained both from the parents and the child; participants were given stickers as incentives. All participants had normal vision and no history of neurological impairment.

Materials

Adults were tested on desktop computers within our lab space on campus. Children were tested on laptops at their schools. The experiment was programmed, designed, and administered through E-Prime software.

Design and Procedure

The same experiment was run on both kids and adults, with the only adaptions being that the instructions were read aloud for children and the children's responses were entered by the experimenter (adults entered their own responses). The study began with instructions on the parameters of the "game" the participant was about to play. The instructions were as follows:

> "You will see a house in the center of the screen. Each house will have four windows with four different curtains, and these curtains will move around and change. There are two kids of houses. There is one kind of house that birds like to live in and another kind

of house that frogs like to live in (and they never like to share!) Paying attention to the curtains will help you figure out which kind of creature likes to live in which kind of house. If you help the animals find their homes, then you will find a prize! Try to collect as many prizes as you can!"

These instructions should explain the game and also indicate that there are four features (the curtains) and that it is advantageous to pay attention to those features, irrelevant of location ("the curtains will move"). In each phase of the experiment, there were two relevant images (two curtains) that made up Category A, which would be linked with one animal, and another two relevant images (curtains) that made up Category B, which would be linked to the other animal. It was randomized between subjects which category was linked to which animal—i.e. for some participants, Category A features would indicate the bird's house and for others Category A features would indicate the frog's house. The images that made up the categories had no internal features in common and were together in a category purely because they were assigned that way. We chose to counterbalance which animal matched up with each category in order to control for any unintended similarities between the images that were the category-relevant features and the images that represented the two animals. Because there were no internal similarities, participants had to learn the categories based solely on repetition of stimuli and accuracy feedback during learning trials. Each house stimulus had four possible positions for features. Two of these positions would have the relevant features that made up one category. The other two positions would have images that were irrelevant features, which did not belong to either category. On either side of the house, there were small, cartoonish images of a frog and a bird. [See Figure 1 for examples of this layout] As mentioned previously, Category A and Category B were each made up of two unique images. The two images that comprised one category were always presented together; at no point did participants see only one of the images that made up a particular category. The participants were not told that some features were relevant to category discrimination and others were not. In total, there were 112 unique stimuli created for this experiment, which all had the same general design.

Each participant began with a basic walkthrough in order to get them accustomed to the visual layout and to understand the process of the experiment. For this walkthrough, the participant was explicitly told what features were relevant, and then they were given eight total trials to practice. First, the participant was told that when they see a pink and a green curtain on a house, that means that it is the bird's house. They were then given four practice stimuli and asked each time what animal lives in the house. In these four practice stimuli, the curtains move around as they do in the experiment proper in order to hint again that the location is not important to category discrimination. The position of the relevant features is totally irrelevant; whether or not the relevant images are present is all that matters towards distinguishing the two categories. (In previous pilot data, many adult participants made that mistake). Next, participants were told that when they see a blue curtain and a purple curtain on a house, that means that it is the frog's house. They were again given four practice stimuli and asked what animal lives in each house. In all eight of these walkthrough trials, there were two irrelevant features that did not make up either category and remained consistent; these were two yellow curtains. We chose these colors strategically to hint that the images need not be internally similar to make up one category or another. (This was also inspired by mistakes observed in pilot data). [The stimuli in Figure 1 are from this walk through. See Figure 2a for category structure.] The participant responses were entered via the computer keyboard, with the right arrow key corresponding to the animal on the right side of the screen and the left arrow key corresponding to the animal on the left side of the screen. Adults entered their own responses, and the experimenter entered responses on behalf of the children as they reported their answers verbally. This remained consistent throughout the entire study.

After this walkthrough, the participants entered Phase 1 and began learning trials. The rules of the "game" were the same, but this time the participants were not told which two images made up Category A or Category B. The irrelevant images and the images that made up the features of each category were all novel stimuli [see Figure 2b.] The participants were told that they must guess at first, and they were given feedback after every response. The feedback was either an image of a prize, if correct, or a text screen that said "Oops! We didn't find a prize! Let's try again!" if incorrect. During learning, the same two images were used as the irrelevant features on every trial. The learning of Phase 1 was comprised of one to three blocks. There were 20 randomized trials in each block. Between each block, there was a chance for participants to take a break. Once the participant hit a criterion of accuracy (17 or more trials correct out of 20), they would move to a testing block. If at the end of the third block the participant had still not reached criterion, they would be moved on to testing anyway. Each participant completed either 20, 40, or 60 trials of learning, depending on how many blocks they needed. [See Figure 3 for a graphical layout of the experiment procedure.] The same 20 stimuli (10 of each category) were shown in each learning block in a randomized order. In the testing phase, the category relevant features remained the same but the irrelevant features changed between eight new images that hadn't been seen before. This was a generalization test to see if participants could maintain the categories that they learned. There were also 20 randomized trials in the testing block. In testing, there were 10 stimuli of each category that were shown in a random order. These stimuli were drawn randomly from a pool of 32 stimuli (16 of each category).

After the testing of Phase 1 was complete, the participants began Phase 2 of the experiment. In this part of the "game", the categories switch from what was previously learned. The four images that formerly made up Category A and Category B now become irrelevant. The two images that were used as irrelevant features during the learning trials of Phase 1 now become split up into two new categories. Category A was then made up of one of the previously irrelevant images and one novel image. Category B was made up of the other previously irrelevant image and a different, novel image. The two stimuli that made up Category A in Phase 1 became the irrelevant stimuli for all of Phase 2 learning. [See Figure 2c.] The participants were alerted that "the curtains have changed!" but they were not specifically told that the features changed in relevancy. Participants were again given feedback during learning and had to learn the new categories through this feedback and repetition. Exactly like Phase 1, participants had between one and three blocks of 20 learning trials. They would move on to testing after either hitting criterion or completing the third block. Like in Phase 1 but with the new category structure, the same 20 stimuli (10 of each category) were shown in each learning block in a randomized order, and, in testing, there were again 10 stimuli of each category that were shown in a random order. These stimuli were also drawn randomly from a separate pool of 32 stimuli (16 of each category). After Phase 2 testing, participants saw a screen that said "You are finished! Thanks for playing!" and then they were given a debriefing explaining what we were studying.

Summary of Results from Experiment 1

We measured accuracy to look for the effects of learned inattention. We hypothesized that adults would use selective attention to learn the categories in Phase 1 (only focusing their attention on the two curtains that were relevant on each house, and thus ignoring the irrelevant features). When we switched the categories in Phase 2, we expected to see a dip in their accuracy as they had to switch their attention back to the features that they had learned to ignore in Phase 1. With child participants, we hypothesized that five year olds would distribute their attention as they learned in Phase 1. Due to this, we were expecting that children would be taking in all features of the stimuli as they learned Phase 1. When the relevancy of the category features switched, we predicted that children would be able to make that change more easily and there would be little or no cost in accuracy.

Across both populations, children and adults, there were mixed results of "learners" and "non-learners." Learning was defined as the accuracy during the testing blocks being significantly above chance. Participants had to learn to accurately discriminate the categories during the first phase in order for us to look for the effects of learned inattention in the second phase. This is because there cannot be a cost of learning incurred after the switch if no learning occurred before it. Participants who learned the categories in Phase 1 were what we refer to as "learners." There were 2 participants deemed "non-learners" that did eventually learn to discriminate categories by the end of Phase 2, but we did not use their data to look for costs of learned inattention.

Of Adult participants, most were able to learn the categories in Phase 1. 75% of adults were learners; this is 15 out of our 21 subjects. The average accuracy for Phase 1 testing (for learners) was very high ($M = 0.95$, $SD = 0.08$, $SE = 0.02$). In comparison, the adult non-learners had an average testing accuracy of 47% ($SD = 0.05$, $SE = 0.02$). Within the adult learners, there was an additional separation. We looked for the cost of learned inattention (and use of selective attention) by comparing the accuracy for the last block of learning in Phase 1 to the first block of learning in Phase 2. (Note: the last block of learning refers to the block in which each participant hit criterion; some participants only needed one block of learning to hit criterion while others needed all three. Averages of accuracy scores were obtained from compiling the accuracy from the last learning block completed before testing.) 40% of the adult learners (n = 6) showed a dramatic cost of selective attention. Their accuracy dropped by 15% to 50% (M = 0.33, SD = 0.15, SE = 0.06). The remaining 60% of adult learners had accuracy so high that the cost of learned inattention was less obvious. Their accuracy dropped by an average of only 6% (SD = 0.08, SE = 0.03). Despite this separation, when we analyzed the data of all adult learners together, there was still a statistically significant cost of learned inattention observed. The average accuracy for the last block of learning in Phase 1 was very high (M = 0.94, SD = 0.05, SE = 0.01). The average accuracy for the first learning block in Phase 2 was much lower (M= 0.78, SD = 0.20, SE = 0.05). [See Figure 4a for graphed block accuracy data from all learners.] This drop in accuracy was statistically significant in a paired-sample t-test ($t(14) = 3.63$, $p < 0.05$). [See Figure 4b for a summary of these statistics.] This significant drop in accuracy we attribute to the use of selective attention in learning Phase 1 categories. We believe that through learned inattention, the learning of Phase 2 categories was partially inhibited. Despite this cost at the start of learning, all adult learners were able to recover. By the end of Phase 2, the average accuracy for testing was back up to 90% (M = 0.90, SD = 0.17, SE = 0.04).

Compared to adults, there were much fewer child participants who were able to learn the categories in Phase 1. Of child participants, 48% were learners; this is 13 participants out of 27. Again, we compared the average accuracies of the last block of learning in Phase 1 to the first block of learning in Phase 2 to look for effects of learned inattention. We predicted that children would distribute their attention and show a more diminished drop (or no drop at all) in accuracy. The average accuracy for the last block of learning in Phase 1 was 89% (M = 0.89, SD = 0.08, SE = 0.02). The average accuracy for the first learning block in Phase 2 was 60% (M= 0.60, SD = 0.19, SE = 0.05). [See Figure 4a for graphed block accuracy data from all learners.] This drop in accuracy was statistically significant in a paired-sample t-test ($t(13) = 5.33$, $p < 0.05$). [See Figure 4c for a summary of these statistics.] This significant drop indicates the use of selective attention. The switch also seemed to affect children more strongly than adults; the average accuracy for Phase 2 testing was 54% (SD = 0.23, SE = 0.06) which indicates that most of the children were not able to recover from the switch. This was all surprising to us as this was not how we expected 5 year olds would behave.

Looking into the child data further, there were several interesting divides. First, only a small amount of the child participants were able to learn the categories. Where does this separation come from? Our hypothesis is that there might be an age or school effect that caused this split. All of the child participants were 5 years old at the time of testing, but some of the children had turned 5 recently and others were almost 6. There is the possibility that somewhere in fifth year of life, there is specific development happening towards children's attention. There might be a difference in attention and learning between older 5 year olds and younger 5 year olds. Due to some missing participant information, there was not enough data to test this potential relationship. However, another possibility is an effect of schooling. Some of the child participants were attending preschool at the time of testing and others were already in elementary school. One hypothesis we have is that the children in elementary school, due to being in school longer, are better at focusing their attention and completing the experiment. This may be due to just being better at taking direction from an authority figure (the experimenter) because they are more familiar with the student-teacher dynamic. Of the child learners, 10 were from elementary schools and 3 were from preschools. Of the non-learners, there were 10 children from preschools and 4 from elementary school. When running a chi-square test of independence, the relation between these variables was significant, X^2 (2, N = 27) = 6.31, $p < 0.05$. [See Figure 4d for a summary of these statistics.] Children from elementary schools were more likely to be able to learn the categories. There could be a number of different reasons that this is true, but it is notable that the relation is significant. We don't know the details of potential age effects, but this effect of schooling would be even more interesting if it didn't correspond with age. That would imply that there was something inherent to what is being done in our school system that influences children's attention.

Another consideration is that the majority of the child learners demonstrated a dramatic drop in accuracy after the switch, but not all. 10 children dropped from an average of 88% accuracy in the last learning block of Phase 1 to an average of 50% accuracy in the first block of Phase 2. This was an average drop of 37% (SD = 0.14, SE = 0.05). The remaining three child learners dropped from an average of 93% accuracy to an average of 90% accuracy. The average drop for these three kids was 3% (SD = 0.10, SE = 0.06). [See Figure 4e for a table containing the relevant accuracy scores for these three participants.] These three children introduce a question. The pattern of the data from this experiment indicates that adults and children seem to all be using selective attention to learn these categories. However, are these three children (that show little drop in accuracy) actually distributing attention? Or, are they more efficient or flexible with their use of selective attention? Are these three kids acting more like adults or more like four year olds? The accuracy data alone is not enough to answer this question.

Experiment 2

Motivation

The use of eye-tracking technology was a natural step forward to continue investigating these phenomena. The benefit of this technology is that there is less of a need for us to assume attention patterns, because we can track where participants are looking on the screen and then know what they are likely paying attention to. Going into this study, we aimed to run the same experiment again with the added eye-tracking software in order to more closely address our original hypotheses about attention and category learning.

Method

Participants

For this experiment, we recruited 20 adult participants. They were all undergraduate students at The Ohio State University. They ranged in age from 18 to 29 years old (M = 20.83, SD = 2.55, SE = 0.57). 19 out of the 20 participants were right handed, and 1 participant was left handed. 16 out of the 20 participants were right eye dominant, and the other 4 participants were left eye dominant. All participants had normal vision and no history of neurological impairment.

Materials

The experiment was re-programmed and administered through software from SR Research. Experiment Builder was used to program and Data viewer was used to analyze eye-tracking data. Adults were tested using the eye-tracker in our lab space on campus. The eye-tracking technology we used was SR Research's EyeLink 1000. This was set up with a remote arm monitor and monocular tracking on each participant's dominant eye. Eye gaze was measured by computing the pupil-corneal reflection at a sampling rate of 500 Hz (meaning 500 gaze data points were collected per second). The eye-tracking device was suspended from the wall (on the remote arm) inside a darkened testing booth. In this booth, the eye-tracking technology was installed on a 1280 x 1024 monitor where the experiment was displayed. In a separate room, the experimenter monitored participants and entered responses using Experiment Builder software installed on two desktop computers. Microphones were used so that the participant and experimenter could communicate, and speakers were located inside the testing booth out of sight of the participant. Responses were said aloud by participants and entered via a keyboard by the experimenter.

Design and Procedure

The same experimental design and procedure was used here as in Experiment 1 (see previous description). All instructions, stimuli, images, etc. were identical to those used in the first experiment. The only difference in design for Experiment 2 was the addition of eye tracking necessities, specifically calibration of the eye-tracker at the start of the experiment and drift correct slides before each trial. In testing blocks in both phases, all 32 stimuli were shown to participants in a randomized order (16 of each category). Additionally, the program was designed so that the same program could be administered with both children and adults, so adult participants were asked to say their answers out loud and the experimenter entered those responses with a computer keyboard in another room. Microphones and speakers were used to communicate between testing room and control room.

Summary of Results from Experiment 2

Accuracy Data:

Of these participants, 95% learned the categories in Phase 1; this is 19 out of the 20 participants. All of the learners had very high testing accuracy in Phase 1 (M = 97%, SD = 0.10, SE = 0.02). As before, we compared the average accuracies of the last block of learning completed in Phase 1 to the first block of learning in Phase 2 to look for evidence of selective attention and learned inattention. The average accuracy for the last block of learning in Phase 1 was 93% (M = 0.93, SD = 0.07, SE = 0.02). The average accuracy for the first learning block in Phase 2 was 87% (M= 0.87, SD = 0.09, SE = 0.02). [See Figure 5b for graphed block accuracy data from learners.] This drop in accuracy, though small, was statistically significant in a paired-sample t-test ($t(18) = 2.87$, $p < 0.05$). [See Figure 5a for a summary of these statistics.] This data also indicated the use of selective attention. Because the difference in accuracy was small, the eye tracking data became very important in establishing the use of selective attention. It was also valuable that these learners were high in accuracy; this new population could potentially clarify the ambiguity in the high scoring adults and children from Experiment 1. We felt that it could be reasonably assumed that if the eye tracking data matched to this accuracy data in the way we predicted, it would give more merit to the accuracy data we have from Experiment 1.

Eye-track Data:

With eye-tracking technology, we wanted to find out where participants were looking, and thus what they were paying attention to, as they learned. We predicted that individuals who were selectively attending would show increased relative looking time towards relevant features, and decreased relative looking time towards irrelevant features. We compared relative looking times, because as people learn the rules of categorization they often get faster with their responses. Due to this, the absolute looking time (towards anything) would likely go down as participants get more confident. In data analysis, we restricted our areas of interest to just the features of the stimuli, and we excluded time spent looking elsewhere in the image.

We analyzed the eye-tracking data for the learners and found that, on average, participants did spend a higher percentage of time looking towards relevant features over irrelevant features. The percentage of "dwell time" that a participant spent fixating on relevant features (M = 0.1359, SD = 0.18297, SE = 0.003) was comprised of the time they spent looking at either of the two relevant features in each stimulus. Similarly, the percentage of time spent looking towards irrelevant features (M = 0.0754, SD = 0.12035, SE = 0.002) was comprised of time spent looking at either of the two irrelevant features. [See Figure 6a for summary statistics] We did not separate one relevant feature from the other, because they never appeared apart. Also, a participant could learn the categories by focusing on only one of the two features and still be correct. The difference found between relative looking time towards relevant and irrelevant features was significant in a paired-sample t-test ($t(5125) = 20.07$, $p < 0.05$). These means were calculated from the percentage of dwell time towards relevant and irrelevant features throughout the entirety of the experiment, including walkthrough trials and all learning and testing trials of both phases.

We then computed the average relative look times towards relevant and irrelevant features across all the blocks of the experiment. (Note: Walkthrough and testing were also considered blocks.) We again adjusted lag to criterion for this data, so we could compare criterion block of Phase 1 to the first block of learning in Phase 2 (as we did for accuracy). [See Figure 6b for table summaries for each block; see Figure 6c for a graph of this information] For relevant features, we found no significant difference between relative looking times before and after the category switch ($t(1975) = 1.007$, $p > 0.05$). However, for irrelevant features, we did find a significant difference between average relative looking times between Phase 1 criterion block and the start of Phase 2 learning ($t(1975) = 5.75$, $p < 0.05$). This means that after the switch, participants were spending more time looking back to previously relevant features. This is likely the cost of learned inattention that we predicted. Additionally, we observed that in the criterion block of learning, when participants are at their highest accuracy, they are looking almost twice as long to relevant features over irrelevant features. This data supports the claim that adults are using selective attention to discriminate these categories.

Discussion and Conclusions

These experiments were largely inspired by a study done with pigeons in the Comparative Cognition Lab at the University of Iowa (Castro & Wasserman, 2014). Their study used the same category features as Phase 1 of my experiment and a similar overall paradigm. Instead of analyzing eye gaze, however, they tracked the pecking rates of the birds. The location of those pecks indicates where the birds are attending. Their study found that pigeons were able to selectively attend to learn categories. In addition, research by Macintosh (1965) has shown that the ability to selectively attend also exists in rats. Knowing that non-human animals are capable of selective attention, it is not that surprising that both 5 year old children and adults could selectively attend despite our original hypotheses.

We initially predicted that children would be distributing their attention during the experiment and would therefore show no evidence of learned inattention or selective attention. We found quite opposite results. The data indicated that the children who were learning the categories were likely all using selective attention. From this, we theorize that the categories we were using may *require* the use of selective attention in order to be learned. This is supported by the fact that the pigeons that learned the categories were also demonstrating selective attention. We further believe that between children and adults (and pigeons and rats) there is variability in the amount of flexibility an individual has with using selective attention. This is a potential explanation for differences found across populations, such as adult participants being able to recover after the switch, while most of the child participants could not. Data also indicated that while 5 year old children may be capable of selective attention, it is not necessarily something that every 5 year old can do. The children may also be more rigid and limited in their use of this potentially newly developing skill.

Finally, eye-tracking data supported the assumption that our accuracy results were correctly reflecting the use of selective attention. Data showed that participants who learned the categories were looking more towards relevant features than irrelevant features. After the category switch, there was also a significant difference in look times towards irrelevant features, indicating that adults continued to look to the previously relevant features even after they became irrelevant. The eye-tracking data suggests that patterns of accuracy we saw in adults were likely indicating the use of selective attention. If this is true, we can assume that the children who showed similar patterns of accuracy to adults were also using selective attention to learn.

It is worthwhile to note, in regards to the eye-tracking data, that there were a few factors that may have weakened the statistics. One factor is that we compressed block accuracy into one value. Generally, costs of attention and differences in looking time would be most evident in the first few trials of Phase 2. The significance of this may have been minimized by considering all of Phase 2 Block 1 learning as one value. Participants had often recovered from the switch by the end of that first learning block in Phase 2 and were back to selectively attending to the newly relevant features. Breaking down the trials into smaller segments than the blocks could have made differences more obvious or more significant. Another factor that potentially influenced our data was that adults have a tendency to use their peripheral vision. This can reduce fixation data. Because the relevant features in my study move around to different positions on the screen, it does somewhat force participants to search the image before they can find the relevant feature and make their decision. However, some adults would look straight to the relevant feature while others would keep their eyes fixated in the center of the screen and make their category decision based on what they saw quickly in their peripheral vision. This is not an issue unique to my experiment, and it is one of the reasons that eye-tracking data is not a perfect measure of attention. When people are fixated on something, it is safe to assume they are paying attention to it. However, not being fixated on something (in the case of peripheral vision) doesn't necessarily mean that they are not attending to anything. While these factors should be considered when evaluating the eye-tracking data, the overall assumptions of this thesis were supported by the combination of eye-tracking and accuracy data across both experiments.

Significance and Future Directions

This project helped contribute to the understanding of selective attention and category learning across development. We were able to observe adults and children using selective attention and suffering its costs. Most notably, this experiment may have identified a test for selective attention. We believe that the children who did not learn the categories, *could not* learn the categories because they were unable to focus their attention. If it is true that the categories we used require selective attention to be learned, this experiment could be used to identify whether or not an individual is capable of selective attention. Having a clear test of whether or not a participant is selectively attending would be very helpful in establishing the development of this cognitive skill. With augmentations, we could potentially use this experimental design to answer questions about when this attention skill emerges, and we might be able to further investigate the flexibility of this skill and differences in attention control within the normal population. To move forward with this project, more data would need to be collected, particularly more child data. Collecting more behavioral data would allow us to further investigate the age or schooling effects. In addition, collecting eye-tracking data with children would be useful to determine what they are actually doing as they learn and how closely they resemble adults.

References

Best, C. A., Yim, H., Sloutsky, V. M. (2013) The cost of selective attention in category learning: Developmental differences between adults and infants. *Journal of Experimental Child Psychology*, 116, 105-119

Best, C. A., Robinson, C., Sloutsky, V. M. (2012) The role of words in cognitive tasks: what, when, and how? *Frontiers in Psychology*. 3, 95

Castro, L., & Wasserman, E. A. (2014). Pigeons' tracking of relevant attributes in categorization learning. *Journal of Experimental Psychology: Animal Learning and Cognition*, *40*(2), 195.

Hoffman, A. B., & Rehder, B. (2010). The costs of supervised classification: The effect of learning task on conceptual flexibility. *Journal of Experimental Psychology: General*, 137, 52-72.

Kruschke, J.K. (1996) Dimensional relevance shifts in category learning. *Connection Science*, 8, 225-247

Kruschke, J. K. (1992). ALCOVE: an exemplar-based connectionist model of category learning. *Psychological review*, *99*(1), 22.

Mackintosh, N. J. (1965). Selective attention in animal discrimination learning. *Psychological Bulletin*, 64, 124-150.

Sloutsky, V. M. (2010). From perceptual categories to concepts: What develops? *Cognitive Science*, 34, 1244-1286.

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Appendix: Figures

Figure 1: Examples of trial layout

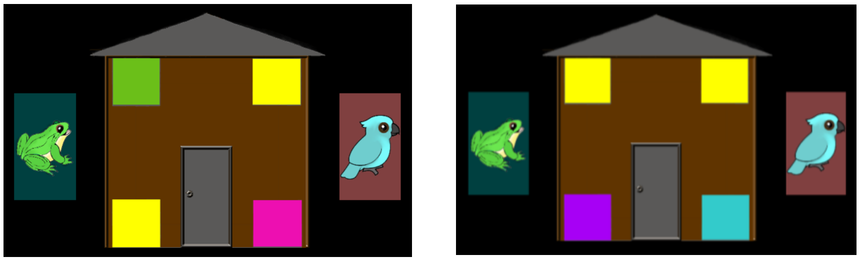


Figure 2a: Category structure of walkthrough trials

Figure 2b: Category structure of Phase 1

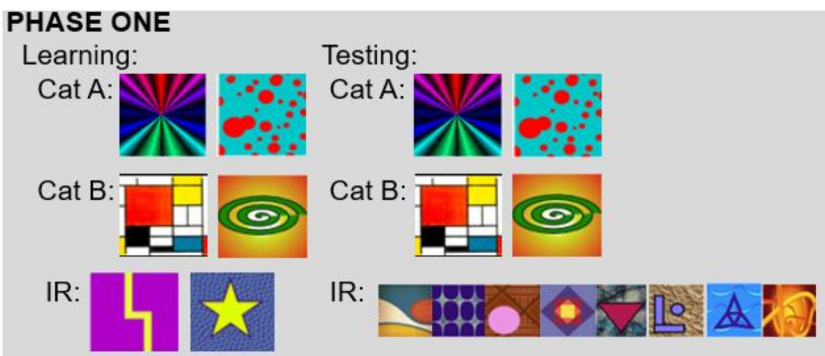


Figure 2c: Category structure of Phase 2

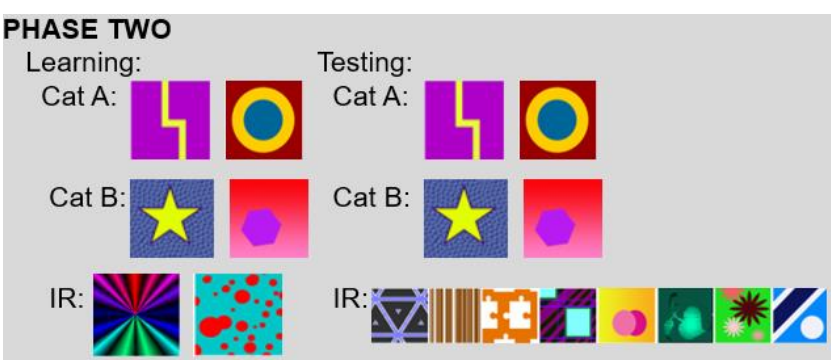


Figure 3: Graphical layout of experiment procedure

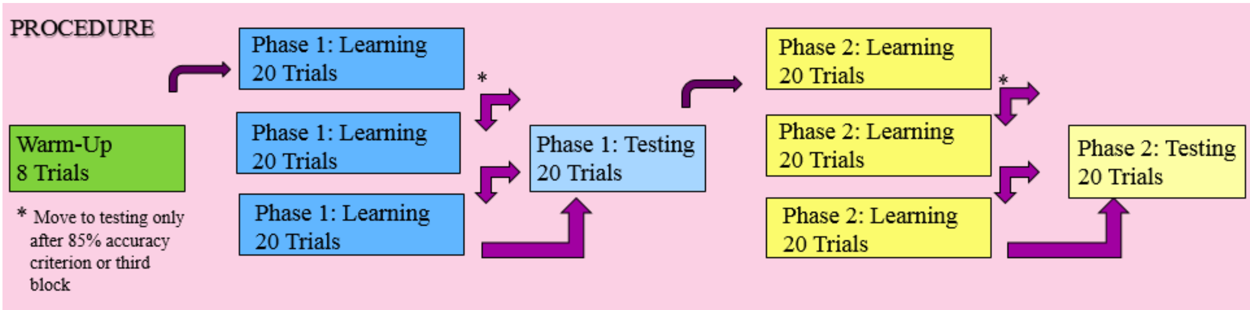
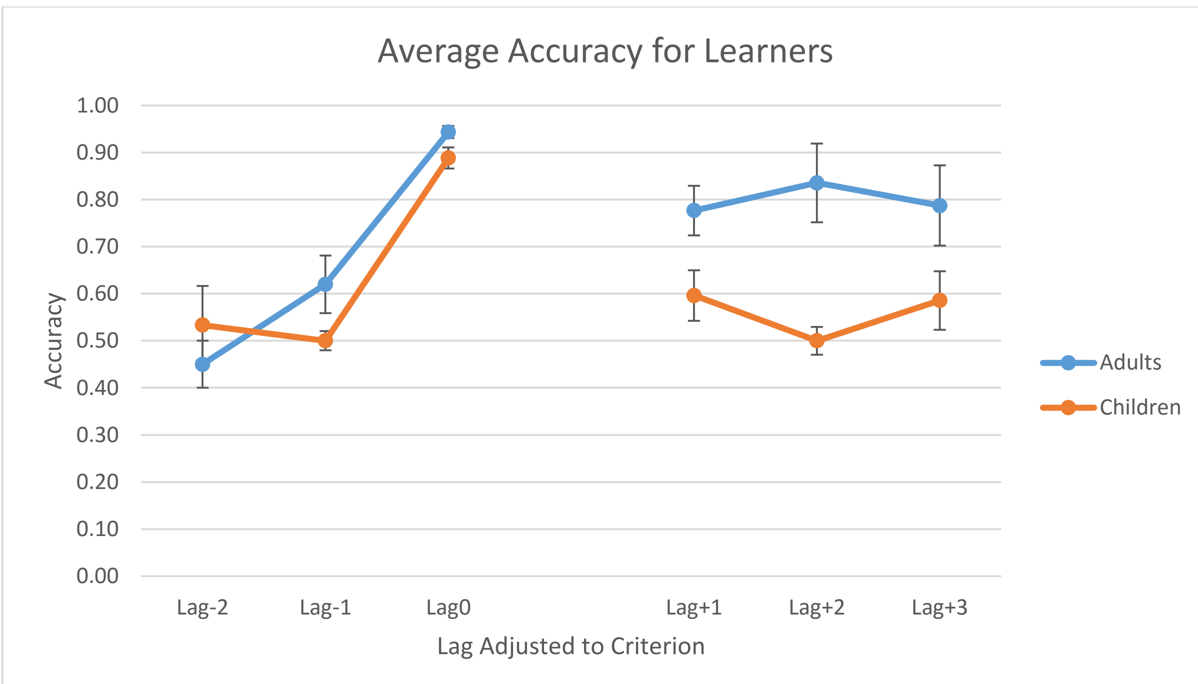


Figure 4a: Chart of block accuracy data for all learners (those who learned the categories in Phase 1)



Because participants did different amounts of learning blocks, the average accuracy data for blocks was graphed after being adjusted to when participants hit criterion. Lag0 refers to the last block before testing; it is the average accuracy of the block in which the criterion accuracy (85% or higher) was reached. Lag-1 refers to the block preceding the block where participants hit criterion, and similarly Lag-2 is two blocks before participants hit criterion. Lag+1 is the first block of learning in Phase 2, and Lag+2 and Lag+3 refer to the second and third blocks of learning, respectively, for Phase 2 (if data exists). **The significant drop in accuracy seen between Lag0 and Lag+1 is the cost we see of learned inattention,** evidence of the use of selective attention. This cost is significant in both adults and children, with children being more strongly affected. This chart graphs average accuracy of learning blocks, the testing blocks were not included.

Figure 4b: Summary statistics from Experiment 1 Accuracy Data - Adults

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	CriterionBlock	.9433	15	.04952	.01279
	Phase2Block1	.7767	15	.20430	.05275

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	CriterionBlock - Phase2Block1	.16667	.17795	.04595	.06812	.26521	3.627	14	.003

Figure 4c: Summary statistics from Experiment 1 Accuracy Data – Children

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	CriterionBlockKid	.8885	13	.08204	.02275
	Phase2Block1Kid	.5962	13	.19307	.05355

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	CriterionBlockKid - Phase2Block1Kid	.29231	.19774	.05484	.17281	.41180	5.330	12	.000

Figure 4d: Chi-square test to analyze school effect

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	6.312[a]	1	.012		
Continuity Correction[b]	4.524	1	.033		
Likelihood Ratio	6.596	1	.010		
Fisher's Exact Test				.021	.016
N of Valid Cases	27				

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 6.26.

b. Computed only for a 2x2 table

School * Learn Crosstabulation

			Learn		Total
			n	y	
School	e	Count	4	10	14
		% within School	28.6%	71.4%	100.0%
		% within Learn	28.6%	76.9%	51.9%
		% of Total	14.8%	37.0%	51.9%
	p	Count	10	3	13
		% within School	76.9%	23.1%	100.0%
		% within Learn	71.4%	23.1%	48.1%
		% of Total	37.0%	11.1%	48.1%
Total		Count	14	13	27
		% within School	51.9%	48.1%	100.0%
		% within Learn	100.0%	100.0%	100.0%
		% of Total	51.9%	48.1%	100.0%

In the above table, 'e' refers to elementary school, 'p' refers to preschool; under 'Learn,' 'y' and 'n' refer to yes and no and indicate if these participants were or were not learners, respectively.

Figure 4e: Table of outlier children

	Criterion Block Accuracy	Phase 2 Block 1 Accuracy	Difference
Child1	0.90	0.90	0.00
Child2	0.90	0.95	-0.05
Child3	1.00	0.85	0.15
Averages	0.93	0.90	0.03

Figure 5a: Summary Statistics from Experiment 2: Accuracy Data

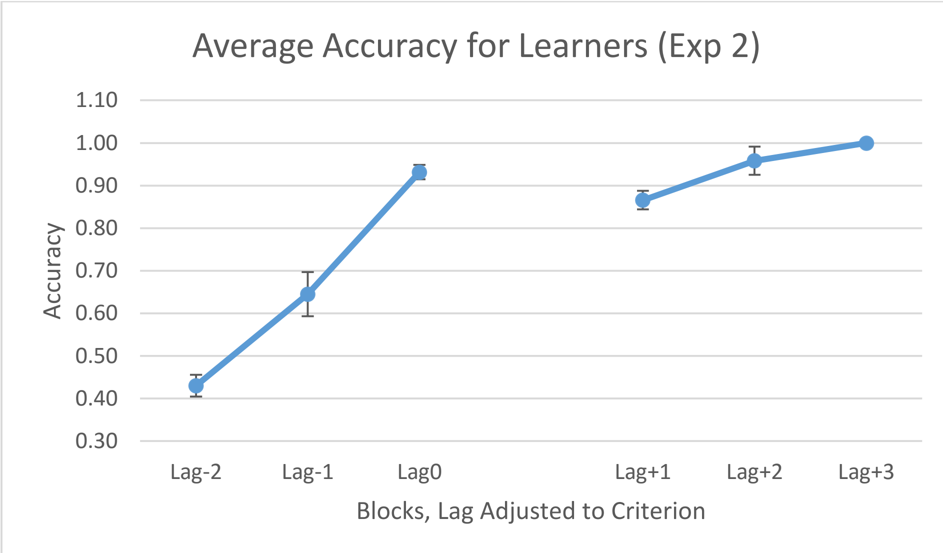
Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	CriterionBlock	.9316	19	.07493	.01719
	Phase2Block1	.8658	19	.09436	.02165

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	CriterionBlock - Phase2Block1	.06579	.10007	.02296	.01756	.11402	2.866	18	.010

Figure 5b: Chart of block accuracy for learners



(Refer to Figure 4a above for clarification on chart labels.) The difference between Lag0 and Lag+1, though small, is statistically significant and is evidence of the use of selective attention.

Figure 6a: Experiment 2: Descriptive Report of Dwell Time on Interest Areas for Irrelevant (I) and Relevant (R) features

Group Statistics

	Relevance	N	Mean	Std. Deviation	Std. Error Mean
Dwell Time (Percent)	R	5135	.1359	.18297	.00255
	I	5136	.0754	.12035	.00168

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference Lower	Upper			
Pair 1	DwellTimePercent - DwellTimePercentIR	.0607255	.2166152	.0030255	.0547942	.0666568	20.071	5125	.000

Throughout the entire experiment, participants looked more on average towards relevant features than irrelevant features. They looked to any of the features only 44% of the time that they were looking at the screen on each trial.

Figure 6b: Average relative looking for blocks, with lag adjusted to criterion

Report

Dwell Time % Relevant Features

Block	Mean	N	Std. Deviation	Std. Error of Mean
0	.103054	304	.1168114	.0066996
1	.110064	200	.1212990	.0085771
2	.114791	400	.1210890	.0060544
3	.142541	758	.1733106	.0062949
4	.151345	1216	.1936893	.0055544
5	.142449	760	.1865026	.0067652
6	.092408	240	.1699587	.0109708
7	.162105	40	.1131133	.0178848
8	.139885	1216	.2134257	.0061204
Total	.136027	5134	.1829874	.0025538

Report

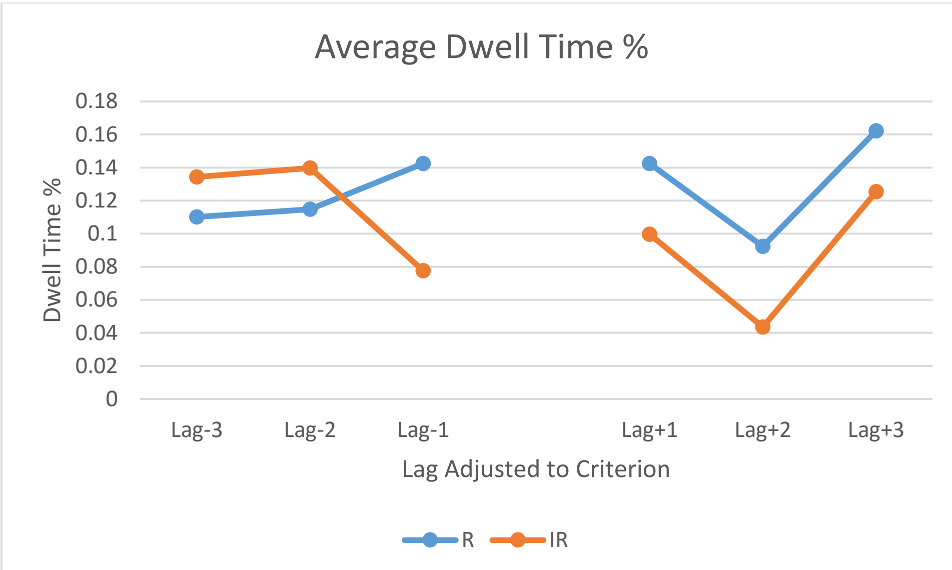
Dwell Time % Irrelevant Features

Block	Mean	N	Std. Deviation	Std. Error of Mean
0	.031252	304	.0680400	.0039024
1	.134341	200	.1486415	.0105105
2	.139791	400	.1493041	.0074652
3	.077591	758	.1153245	.0041888
4	.067644	1216	.1118376	.0032072
5	.099609	760	.1324739	.0048053
6	.043659	240	.1017197	.0065660
7	.125402	40	.1150202	.0181863
8	.051697	1216	.1058210	.0030346
Total	.075461	5134	.1203654	.0016799

Block Numbers: 0 = Walkthrough; 1,2,3 = Blocks of Learning in Phase 1; 4 = Testing in Phase 1; 5,6,7 = Blocks of Learning in Phase 2; 8 = Testing in Phase 2

Like before, this data was calculated with lag adjusted to when participants hit criterion, i.e. if a participant hit criterion in their first block of learning, that block was coded as '3' instead of '1'. The first report table is for relevant features, and the second report table is for irrelevant features. The categories switch occurs between 4 and 5, there is not a significant change in look time to relevant features, but there is a significant difference in look times to irrelevant features. N refers to the values used to calculate the means. There were the same N values for the relevant and irrelevant tables, because the data report included the percentage value of look times for each of the four features for each trial (absence of looking time was coded as 0, not discarded).

Figure 6c: Graph of Average Percent Dwell Time by block



Again, the lag was adjusted to criterion (see previous graphs for explanation).
As explained in the table above, there is a significant difference in relative dwell time on irrelevant features after the category switch, but there is no significant difference for relevant features. We do see indications of the use of selective attention. Particularly in Lag-1, when participants are at their highest accuracy, they are looking almost twice as long to relevant features over irrelevant features. The significant increase in average percentage of dwell time towards irrelevant features between Lag-1 and Lag+1 are demonstrated results of participants looking more towards features that were previously relevant.